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# CERES-Maize and CERES-Sorghum for modeling growth, nitrogen and phosphorus uptake, and soil moisture dynamics in the dry savanna of West Africa

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ABSTRACT

Sustainable production practices are needed to enhance water and nutrient use efficiencies in the cropping systems of West Africa, especially in face of predicted climate change for the region. Crop simulation models may assist in exploring alternative management systems for optimizing water and nutrient use efficiencies, increasing crop production, and easing food insecurity. The twofold objectives were: (i) to access the ability of the CERES-Maize and CERES-Sorghum models for predicting yields, nitrogen (N) and phosphorus (P) uptake, and in-season soil water and N dynamics during maize and sorghum growth; (ii) to use the models to assess the effects of different nutrient management strategies on soil C and N, and crop water and N use efficiencies considering 30 years of historical weather variability in the dry savanna agro-ecological zone of northern Benin, West Africa. Both models were calibrated with data from a researcher-managed field trial (2014) and validated with independent findings (2015). The models were next evaluated with datasets collected from researcher- and farmer-managed field trials conducted under rainfed and supplementary irrigation conditions (2014–2015). The parameterized CERES-Maize and CERES-Sorghum models accurately predicted biomass accumulation with a normalized root mean square error (nRMSE) of 18% and 17%, respectively, and an index of agreement (d) of 0.98 for both crops in non-nutrient- and non-water-stressed conditions. Under rainfed and rainfed with supplementary irrigation conditions, both with and without mineral fertilizer application, CERES-Maize predicted biomass accumulation with nRMSE (d) of 10–22% (0.96–0.99), while CERES-Sorghum reached accuracies of 13–29% (0.97–0.99). Grain yield was simulated with nRMSE (d) of 19% (0.93) and 15% (0.89) by CERES-Maize, and 16% (0.91) and 15% (0.80) by CERES-Sorghum in researcher-managed and farmer-managed fields, respectively. CERES-Maize predicted reasonably well nutrient uptake with nRMSE (d) ranging from 14 to 40% (0.89–98) for N and between 24 and 49% (0.90–0.98) for P. Similarly, CERES-Sorghum simulated N uptake with nRMSE of 17–49% and d-values of 0.87–0.98, and P uptake with nRMSE of 42–62% and d-values of 0.82–0.93. Values of nRMSE (d) between predicted and measured in-season soil water and N dynamics were 6–13% (0.61–0.87) and 46–58% (0.61–0.76) with CERES-Maize, and 14–20% (0.75–0.89) and 35–56% (0.62–0.82) with CERES-Sorghum, respectively. The models simulated improved soil organic C and inorganic N, water and N use efficiencies, and grain yields with the integrated soil-crop management system compared to un-amended soil and high mineral fertilizer use options under 30 years of weather variability. Both models are thus appropriate tools not only to explore potential impacts of predicted climate change on soil water and nutrient use efficiencies, but also to frame more sustainable intensification measures in the maize- and sorghum-based production systems of West Africa.

## 1. Introduction

Declining agricultural productivity, demographic growth, urbanization, and changing consumption habits are major drivers of the increase in the demand for food and feed in West Africa (Garrity et al., 2010; Schlecht et al., 2007; Wheeler and von Braun, 2013). The trends for more demand are further challenged by dwindling resources as manifested by widespread soil fertility depletion and evidenced by low

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soil organic matter (Schlecht et al., 2007) and chronic N and P deficiencies (Bationo et al., 2012). Furthermore, consent exists that the predicted changes in climate and agricultural land use will adversely alter nutrient dynamics (Whitehead and Crossman, 2012), and likely exacerbate the impacts of soil fertility depletion on crop productivity and resource use efficiency (Wu and Ma, 2015). This, in turn, threatens the diversity of the prevailing cropping systems (Callo-Concha et al., 2013), which usually are dominated by staple crops. Therefore, unless action is taken, agricultural land degradation and increasing climate variability will jeopardize food security in West Africa (Wheeler and von Braun, 2013), particularly the availability of maize and sorghum, which are major local staple food crops (Garrity et al., 2010). Under the current conditions of food insecurity and limited access to and affordability of production factors (Wheeler and von Braun, 2013), there is an urgent need to improve resource use efficiencies and yields in smallholder production systems (Wu and Ma, 2015). Hence, sustainable intensification practices are required in the region (Drechsel et al., 2015; Vanlauwe et al., 2014) to ensure production of sufficient, affordable, and nutritious food without compromising the environment.

Field experimentation has been pivotal in assessing the effects of single or multiple factors on crop productivity. However, given the growing costs of conducting multi-level, multifactorial, and long-term field experiments to respond to the existing complexities in soil-plant-climate interactions, complementary approaches are needed. Process-based models are recognized to complement empirical data collection to support decision-making (Tsuji et al., 2013) concerning not only crop responses to soil fertility management, but also the framing of alternative measures to increase the resilience of production systems. While a wide array of simulation models have been assessed for their use in West Africa (Akinseye et al., 2017; Webber et al., 2014), the Decision Support System for Agrotechnology Transfer (DSSAT) – Cropping System Model (CSM) (Jones et al., 2003) appears promising to simulate soil-plant-climate interactions in this region. Reportedly, CSM-CERES-Maize and CERES-Sorghum of the DSSAT can simulate growth, development, and yield in response to weather conditions and soil/crop management (Hoogenboom et al., 2015). They are also recognized to simulate soil water (Ritchie, 1998) and N-balance (Godwin and Singh, 1998) in cropping systems and climate change impacts on crop production (White et al., 2011). Both CERES-Maize and CERES-Sorghum have been extensively tested in terms of crop growth and yield predictions and N fertilizer management in India (Liu et al., 2013; Yang et al., 2011), Togo (Dzotsi et al., 2003), Ghana (Fosu et al., 2012; McCarthy et al., 2012), Mali (Akinseye et al., 2017), Nigeria (Adnan et al., 2017; Jagtap et al., 1993; Jibrin et al., 2012), and Benin (Igue et al., 2013). However, these models have hardly been screened in terms of soil water and nutrient dynamics under typical environment of the dry savanna regions of West Africa. While it has been postulated that seasonal soil moisture dynamics potentially affect the soil supply of N and P (Bationo et al., 2012) and crop nutrient uptake (Buerkert and Hiernaux, 1998), neither processes have been modeled by CSM-CERES and therefore do not yet support the framing of better soil-crop and water management options in this region.

Recent improvements enable CERES-Maize and CERES-Sorghum to respond to conditions of low N and P (Dzotsi et al., 2010; Gijsman et al., 2002; Porter et al., 2009), which are typical for the production environment in the dry savanna zone of West Africa, including northern Benin. However, before exploiting the potential of these models to predict the consequences of climate change on crop growth, development, soil water dynamics and nutrient balances, they must be parameterized and evaluated for these agro-ecological conditions and must prove to be sufficiently robust to respond to these typically N- and P-poor environments. The twofold objectives were: (i) to access the ability of the CERES-Maize and CERES-Sorghum models for predicting yields, nitrogen (N) and phosphorus (P) uptake, and in-season soil water and N dynamics during maize and sorghum growth; (ii) to use the models to assess the effects of different nutrient management strategies on soil C and N, and crops water and N use efficiencies considering 30 years of historical weather variability in the dry savanna agro-ecological zone of northern Benin, West Africa.

## 2. Materials and methods

### 2.1. Description of the CERES-Maize and CERES-Sorghum models

CSM-CERES-Maize and CERES-Sorghum within the DSSAT Version 4.6 (Hoogenboom et al., 2015) are process-level, comprehensive models to simulate crop growth, development, and final grain yield of maize and sorghum. The models simulate growth and development using a daily time-step routine from sowing to maturity or a specified harvest time based on physiological processes that describe crop responses to soil and weather conditions. Phenological development and growth are specified by cultivar-specific genetic coefficients depending on the photoperiod, thermal time, temperature response, and dry matter partitioning. Both models account for temperature effects on crop growth and grain filling rate based on cardinal temperatures, assuming trapezoidal responses and an optimum temperature of 34 °C (Kumudini et al., 2014; White et al., 2015). Potential dry matter production is assumed to be proportional to the photosynthetically active solar radiation absorbed by a crop canopy. The actual dry matter production on a given day is constrained by suboptimal air temperature, soil water deficits, or N and P deficit factors for crops. The dry matter simulated is partitioned into different parts of the plant on the basis of temperature and phenological stage of the crop (Hoogenboom et al., 2010; Ritchie et al., 1998). Soil water, N, P, and organic C dynamics and their interactions with crop management are determined in subroutines that are shared by all crops in CSM. More detailed descriptions of the soil water, N, and C balance dynamics are found in Ritchie (1998) and Godwin and Singh (1998), but elements key to the present study are briefly described hereafter.

The soil-water balance component simulates the daily water balance processes, i.e. infiltration (rainfall and irrigation), surface runoff, drainage, evaporation from the soil surface, and water extraction by the plant. The downward flow of soil water to lower soil layers occurs according to a cascading approach based on the water content between saturation (SAT) and drained upper limit (field capacity, DUL); this flow is a determinant in computing the share of nitrate leaching (Ritchie, 1998). The CERES-N balance routine for upland cropping systems simulates the turnover of soil organic matter and the decay of crop residues with the associated mineralization and/or immobilization of N, the major N loss processes (nitrification of ammonium and associated denitrification), and the contribution to the N balance made by mineralization. The model neither simulates losses by ammonium volatilization or ammonium exchange equilibria nor nitrogen dioxide ($N_2O$) and dinitrogen ($N_2$) emissions (Bowen and Baethgen, 1998; Gijsman et al., 2002; Godwin and Singh, 1998). Recent adaptation of CENTURY-based soil organic matter-residues module for DSSAT-CSM allows better understanding of soil organic nutrient processes (Gijsman et al., 2002; Parton et al., 1988; Porter et al., 2009).

The routine simulates plant N uptake and distribution within crops, the remobilization during grain filling, and the effects of N deficiency on crop growth processes. The N-deficit demand is defined as the difference between a critical N concentration and an actual N concentration in the plant. The potential N uptake is the product of soil inorganic N concentrations, root length density, maximum N uptake per unit root length, and a soil water factor. The actual N uptake is determined as the lesser of either potential crop N demand or potential N uptake. The NFACT submodel calculates N-deficit factors in maize and sorghum.

The soil-plant P-submodule integrates inorganic P pools (labile, active, and stable) and organic P pools (active and stable) with plant P uptake (Dzotsi et al., 2010). The P-submodule computes daily P transformation between the pools in the roots and non-roots zones of the soil. The P uptake is constrained by the minimum of plant demand and

soil P supply capacity, and the minimum of daily N:P ratio (Dzotsi et al., 2010). Since the rates of transformation of N and P are very much influenced by soil water status, the simulation of N and P dynamics requires that the soil water content is well simulated.

### 2.2. Field experiments

Three field experiments were conducted during the 2014 and 2015 cropping seasons near the village of Ouri Yori (10°49′16″N, 1°4′7″E) in the Dassari catchment (10°44′0.15″–10°56′0.6″ N, 01°01′37″–01°11′33″E), North Benin, in West Africa. This catchment is representative of the dry savanna agro-ecological conditions and experiences a wet period usually from May to October and a dry period from November to April. Over 1986–2015, the total annual rainfall amounted to 1099.5 ± 195.8 mm in the study area. The annual mean for minimum temperature, maximum temperature, and solar radiation was 21.4 ± 0.6 °C, 33.7 ± 0.7 °C, and 19.5 ± 0.5 MJ $m^{-2}$ $d^{-1}$, respectively over the same period. The major vegetation type in the catchment encompasses woodlands, woody shrubs, grasses, and gallery forests (Wezel et al., 1999). The experiments were conducted on the three dominant soil types in the catchment, i.e. Gleyic Alisols, Dystric Plinthosols, and Ferric Luvisols (IUSS Working and Group, 2014; Steup, 2016) (Table 1). The three field experiments as well as the rationale of the soil fertility management treatments tested are described here addressing the treatments that included maize and sorghum as test crops.

#### 2.2.1. Experiment-1: researcher-managed on-farm trial for calibrating and validating the models

Experiment-1 was set up to collect essential data for calibrating and validating both models. It was conducted on a loamy sand soil classified as a Gleyic Alisols (Table 1). The experiment was implemented as a randomized complete block design (RCBD) with high mineral fertilizer use under sole maize (cv. EVDT-97 STR) and sorghum (cv. Local) as treatments with three replications. Existing fertilizer recommendation rates for the tested crops are 44 kg N $ha^{-1}$, 15 kg P $ha^{-1}$, and 17.5 kg K $ha^{-1}$ (Igue et al., 2015; Saidou et al., 2012). In the high mineral fertilizer treatment, the recommended fertilization rates were thus almost doubled to test the responses of both crops under nutrient-stress-free conditions, and assess the effectiveness of increased fertilizer rates. All plots (6 m × 5 m) were tilled using an animal-drawn plow before planting. During the tillage, previous crop residues were manually removed while the remaining surface liters were incorporated. Maize and sorghum were seeded on July 19th in 2014 and June 23rd in 2015 at a density of 6 plants $m^{-2}$ (80 cm × 40 cm). The plots were regularly weeded manually to keep them weed free. Nitrogen (80 kg N $ha^{-1}$) was applied as urea (46%) through a split application to all maize and sorghum plots at a rate of 40 kg N $ha^{-1}$ at 3 and 6 weeks after planting of both crops. Along with the first N- application, P was applied as triple superphosphate (46% $P_2O_5$) and K as potassium chloride (60% $K_2O$) at rates of 26 kg P $ha^{-1}$ and 30 kg K $ha^{-1}$, respectively. All fertilizers were applied manually and next incorporated to approximately 8 cm depth at ca. 10 cm from the seedlings. Supplementary irrigation (1.5–8 mm per event of watering) was applied during dry spells to minimize water stress. In total 7 and 9 applications occurred in 2014 and 2015 over a period of 30 and 38 days after planting (DAP), respectively.

**Measurements:**

The number of days to 50% anthesis and physiological maturity were recorded for 15 plants randomly selected from the inner rows of each plot. In-season aboveground biomass (AGB) was determined every fortnight from 20 DAP until final harvest. At each sampling event, whole plants from three planting holes of each plot were harvested for the determination of the total dry matter (DM). After harvest, the biomass was chopped and mixed, the fresh weight recorded, and a sub-sample taken of which the fresh weight was recorded as well. The sub-samples were oven-dried at 70 °C till constant weight and the DM content estimated and extrapolated to kg DM $ha^{-1}$.

After physiological maturity, maize ears and sorghum panicles were harvested from the inner two rows of each plot for the assessment of grain yields. The fresh weight of the harvested grain was recorded with a portable scale, sampled and the sub-sample oven-dried at 70 °C until constant weight. The final grains yields were converted to kg DM $ha^{-1}$. The total biomass from the inner two rows (net plot) was cut and weighed fresh. Next, a sub-sample was taken, weighed, and oven-dried at 70 °C until constant weight. The total DM for the plot was extrapolated to kg DM $ha^{-1}$.

#### 2.2.2. Experiment-2: researcher-managed on-farm trial for evaluating the models

Experiment-2 was a researcher-managed trial conducted in 2014–2015 on a Gleyic Alisols (Table 1). In 2014, the treatments comprised two soil fertility management options, an un-amended soil (no fertilization) as control and an integrated soil-crop management practice that combined the recommended mineral fertilizer rates (Section 2.2.1) with the return of crop residues. The integration of crop residues and inorganic fertilizers is reportedly a potential option for sustainable soil fertility restoration in the region (Lal, 2006; Schlecht et al., 2007). In all cases maize and sorghum were used as test crops. The experimental design was a RCBD with three replications. Treatment plots measured 7 m × 4.2 m. In 2015, the experiment was re-designed as a factorial combination of the two soil fertility management options and two water management levels (rainfed and rainfed + supplementary irrigation). The objective of the supplementary irrigation practice was to examine the influence of moisture availability, notably at the onset of the rainy season, on N and P dynamics and the uptake of both minerals by crops. Supplementary irrigation occurred during dry spells only and through drip irrigation. At the onset of the 2014 and 2015 growing seasons, all crop residues were incorporated into the soil on the integrated soil-crop plots designated to receive a fertilizer application. The previous crop residues were removed manually from the un-amended plots (no fertilization). Crops were planted on July 4th in 2014 and June 25th in 2015. At 21 DAP during both seasons,

**Table 1**
Physical and chemical characteristics of the soils at the experimental sites used for calibrating and evaluating the CERES-Maize and CERES-Sorghum models.
Source: Datasets from Steup (2016).

| Soil | Layer (cm) | pH | Org. C (%) | Total N (%) | Bray 1P (ppm) | CEC Cmol (+) $kg^{-1}$ | Sand (%) | Silt (%) | Clay (%) | Bulk density ($gcm^{-3}$) |
|---|---|---|---|---|---|---|---|---|---|---|
| Gleyic Alisols | 20 | 5.9 | 0.28 | 0.05 | 1.0 | 6.2 | 82.4 | 15.2 | 2.5 | 1.4 |
| | 40 | 6.1 | 0.14 | 0.04 | 1.0 | 7.8 | 82.1 | 12.8 | 5 | 1.4 |
| | 60 | 5.9 | 0.13 | 0.06 | 1.0 | 5.8 | 79.4 | 10.7 | 10.9 | 1.4 |
| Dystric Plinthosols | 20 | 6.5 | 0.70 | 0.09 | 3.0 | 6.4 | 75.0 | 19.9 | 4.0 | 1.5 |
| | 40 | 6.8 | 0.18 | 0.06 | 1.0 | 8.6 | 77.2 | 19.4 | 4.5 | 1.5 |
| | 60 | 7.0 | 0.17 | 0.05 | 2.0 | 7.2 | 63.9 | 26.4 | 10.8 | 1.4 |
| Ferric Luvisols | 20 | 6.6 | 0.68 | 0.08 | 4.0 | 8.5 | 68.7 | 21.1 | 4.8 | 1.5 |
| | 40 | 6.4 | 0.31 | 0.06 | 3.0 | 4.6 | 63.1 | 29.3 | 9.3 | 1.5 |
| | 60 | 6.5 | 0.23 | 0.06 | 1.0 | 8.7 | 27.9 | 32.9 | 31.2 | 1.5 |

21 kg N ha$^{-1}$, 15 kg P ha$^{-1}$, and 17.5 kg K ha$^{-1}$ were applied as urea, triple superphosphate, and potassium chloride, respectively. A second N fertilizer dose (23 kg N ha$^{-1}$) was applied as urea at 40 DAP. Both experiments were kept weed free by regular hand weeding until harvest. The quantities of water applied per irrigation were 1.7, 2.0, 6.7, 3.3, 10.0, 6.7, and 6.7 mm at 2, 4, 14, 20, 22, 23, 30, 35, and 36 DAP, respectively.

**Measurements:**

In 2014, no in-season biomass accumulation assessment occurred. In 2015, in-season biomass dynamics were monitored weekly from 13 to 34 DAP. Thereafter, the measurements were made bi-weekly until final harvest. The DM at each event was determined as described previously (Section 2.2.1). In-season soil water content was measured from the 0–20, 20–40, and 40–60 cm depth of each plot from 20 DAP until harvest in synchronization with biomass accrual measurements. Soil water was measured with a HH2 moisture meter connected to a PR2/6 profile probe (Delta-T Devices Ltd) that was calibrated for the experimental site. One access tube was installed in each plot to a depth of 1.10 m. Probe reading was taken at 10 cm depth intervals down to 40 cm depth and thereafter at 20 cm intervals to 1.10 m. Soil samples were taken from the 0–20, 20–40, and 40–60 cm soil layers at the same time as biomass measurements. Composite subsamples from each depth were analyzed colorimetrically for soil $NO_3$-N concentrations (IITA, 1982).

At final harvest each year, maize ears and sorghum panicles were harvested from the inner two rows (8.0 m$^2$) of each plot for grain yield assessments as described in Section 2.2.1. The final AGB-DM was estimated by cutting and weighing all stover after the removal of ears and panicles. A sub-sample of the stover was taken, weighed, and oven-dried at 70 °C until constant weight. The sample dry weights were used to estimate the total biomass.

The in-season AGB samples, as well as grain and stover samples of both crops at final harvest, were ground using a Wiley mill and sent for chemical analyses. Total N and P concentrations were determined colorimetrically in an auto-analyzer as reported by Anderson and Ingram (1993). The resulting concentrations allowed for estimating total N and P in the AGB, and grain and stover at harvest. The total N and P uptake (kg ha$^{-1}$) at harvest were estimated by adding grains and stovers uptake.

#### 2.2.3. Experiment-3: farmer-managed on-farm trials for evaluating the models

Experiment-3 was conducted on six fields (0.5–1.5 ha) of different farmers selected to cover all three dominant soil types (Table 1). Three farmers intercropped maize with local cowpea whilst three other farmer intercropped sorghum with local cowpea. The cultivation practices were monitored throughout both cropping seasons. The three farmers for each cropping system were considered as replications. The objective of experiment-3 was to record in detail farmers' practices with respect to their crop and soil management and compare these to the practices under the researcher-managed fields. This allowed for an evaluation of the robustness of the CERES-Maize and CERES-Sorghum while assuming farmers' circumstances. Hence, farmers decided on all management practices while researchers documented them. All fields were tilled using bullock plows and sprayed with glyphosate at a rate of 300–600 g a.i. ha$^{-1}$ as part of field preparation. The planting dates in 2014 varied from July 18th – 31st, and June 23rd – July 25th in 2015. The planting densities at emergence varied according to farmers, but were relatively similar, ranging from 5 to 7 plants m$^{-2}$. Farmers fertilized only maize fields using a compound fertilizer and urea. Fertilizer application rates ranged from 12 to 47 kg N ha$^{-1}$, 4–33 kg P ha$^{-1}$ and 5–39 kg K ha$^{-1}$. Weeds were controlled by farmers using hand hoes.

**Measurements:**

In each field of the farmers, researchers delineated three rectangular plots (8.0 m$^2$) at the beginning of the cropping season to monitor phenological stages and assessing yield at harvest. Additional observations and measurements on each field were kept to a minimum but sufficient to quantify all input parameters/variables as demanded by both CSM models. The monitoring of the output variables permitted the evaluation of model predictions. All management practices including dates of planting, weeding, and fertilizer applications were recorded as well as the type and amount of fertilizer used. Plant population at emergence and final harvest were also recorded. Environmental characteristics such as soils data (Table 1) and weather data were recorded as well. During the two growing seasons, daily rainfall (mm), minimum and maximum air temperatures (°C), and solar radiation (MJ m$^{-2}$ d$^{-1}$) were measured at the experimental site with a Campbell Advanced Weather Station (CR1000) (Steup, 2016). All the sites of the three experiments were located within a 0.5–2 km radius around the weather station. After physiological maturity, crops were harvested on the three delineated sub-plots for grain yield and biomass assessment. The plant density at harvest ranged from 3 to 6 plants m$^{-2}$ for the main crops. The density of cowpea at harvest amounted to less than 1 plant m$^{-2}$, reflecting more a situation of a "pure" maize and sorghum stand than that of a purposely designed intercropping stand. Therefore, the "intercropping" systems were analyzed as sole production systems.

### 2.3. Model calibration

#### 2.3.1. Calibration of genetic coefficients

The 2014 dataset of experiment-1, involving high use of mineral fertilizer and supplementary irrigation to minimize nutrient and water-stress, was used for the model calibration. The genetic coefficients of each crop cultivar were manually adjusted to reach an accurate goodness of fit between simulated and measured dataset. The calibration for maize was based on an existing maize cultivar included in DSSAT, namely AB-11-TG. The default coefficients for the thermal time from emergence to the end of juvenile phase (P1) was reduced to match the observed anthesis of the maize cv. EVDT-97 STR used. The thermal time from silking to physiological maturity (P5) was decreased to match the observed physiological maturity, while the maximum number of kernels (G2) and kernel filling rate (G3) were adjusted to match the observed grain yield and biomass (Table 2).

Likewise, for sorghum, the default coefficients of an existing sorghum cultivar in DSSAT, cv. W. African, were used as starting points to calibrate the local sorghum cultivar. The thermal time from seedling emergence to the end of the juvenile phase (P1), the critical photoperiod (P2O), and extent of delay in phasic development leading to panicle initiation (P2R) were adjusted to match the observed anthesis of the local sorghum cultivar. Next, the thermal time from grain filling to

**Table 2**
Genetic coefficients of maize cv. EVDT-97 STR after calibration and used during validation of CERES-Maize.

| Codes | Definition | Default values AB-11-TG | Calibrated EVDT-97 STR |
|---|---|---|---|
| P1 | Thermal time from seedling emergence to the end of the juvenile phase (> 8 °C in degree days) | 250 | 210 |
| P2 | Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above 12.5 h | 0.1 | 0.10 |
| P5 | Thermal time from silking to physiological maturity (degree days) | 620 | 580 |
| G2 | Maximum possible number of kernels per plant | 920 | 900 |
| G3 | Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day) | 8.5 | 9.23 |
| PHINT | Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances. | 55 | 55 |

**Table 3**
Genetic coefficients of sorghum cv. local after calibration and used during validation of CERES-Sorghum.

| Codes | Definitions | Default values W. African | Calibrated local |
|---|---|---|---|
| P1 | Thermal time from seedling emergence to the end of the juvenile phase | 413 | 650 |
| P2 | Thermal time from the end of the juvenile stage to tassel initiation under short days (degree days above TBASE) | 102 | 102 |
| P2O | Critical photoperiod or the longest day length (in h) at which development occurs at a maximum rate | 13.6 | 13 |
| P2R | Extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P2O | 40 | 100 |
| PANTH | Thermal time from the end of tassel initiation to anthesis (degree days above TBASE) | 617.5 | 617.5 |
| P3 | Thermal time from to end of flag leaf expansion to anthesis (degree days above TBASE) | 152.5 | 152.5 |
| P4 | Thermal time from anthesis to onset of grain filling (degree days above TBASE) | 81.5 | 81.5 |
| P5 | Thermal time from beginning of grain filling to physiological maturity (degree days above TBASE) | 640 | 500 |
| PHINT | Phylochron interval; the interval in thermal time between successive leaf tip appearances (degree days) | 49 | 49 |
| G1 | Scaler for relative leaf size | 3 | 2 |
| G2 | Scaler for partitioning of assimilates to the panicle (head) | 6.5 | 5 |

physiological maturity (P5) was decreased and finally the scaler for the relative leaf size (G1) and for the partitioning of assimilates to the panicle (G2) were calibrated for grain yield and final biomass (Table 3).

After the adjustment for anthesis and physiological maturity, the soil fertility factor for photosynthesis (SLPF) was calibrated so that the simulated top weight matched the initial slope of the observed AGB. The SLPF value needed to be set to 0.98, which is slightly less than the default value of 1. The calibrated models were validated against the 2015 dataset of experiment-1 without a re-calibration of the cultivar specific coefficients.

To account for differences in soil fertility between sites for experiment-1 (used for model calibration) and experiments-2 and 3 (used for model evaluation), one treatment was selected on the different soil types. Here the default SLPF was manually adjusted such that simulated final grain yields were close to measured values in the two seasons. Therefore, the SLPF value for experiment-2 was reduced from 1 (default value) to 0.75 while for experiment-3 the SLPF were reduced to 0.65 on Gleyic Alisols, 0.55 on Dystric Plinthosols, and 0.50 on Ferric Luvisols. The calibrated SLPF values were used to run the models for all treatments on each site without further modification.

#### 2.3.2. Soil water-holding characteristics

The default soil water-holding characteristics required by the models (e.g. DUL, lower limit (LL), SAT, saturated hydraulic conductivity (SWCN), root weighting factor (WR), runoff curve number (CN2), and drainage coefficient (SWCON)) were initially calculated by inputting soil texture, bulk density, soil organic carbon and other information (Table 1) into the DSSAT soil creation utility program. These estimated soil water-holding characteristics were next modified to make them more specific for the site of experiment-2. The default values of SAT were first optimized for each layer by using total porosity values obtained during bulk density measurements for the calibration of the soil moisture probe for the site. Measured soil water content under rainfed conditions without fertilization enabled to estimate the LL and DUL by adjusting the default values to match the lowest water content during drying cycles or when the soil water content remained constant for 2–3 days after a rainfall event for each soil layer. Finally, SWCN, SWCON, CN2, and WR were defined by adjusting the default values to match the measured soil water contents. Table 4 shows the calibrated soil water-holding characteristics used during the runs of the CERES-Maize and CERES-Sorghum under all scenarios: rainfed, supplementary irrigation, with and without fertilizers and combinations thereof.

### 2.4. Model input data

The soil input files were created by inputting measured soil properties data, such as soil texture (percent silt, clay, and sand), soil bulk density, pH, organic carbon, total N, available phosphorus, and CEC for each researcher- and farmer-managed fields (Table 1) into the soil file creation utility program (SBuild) of the DSSAT software.

Weather files for 2014 and 2015 were created using daily minimum and maximum air temperatures, rainfall, and solar radiation recorded at the experimental site with the Weatherman utility program in DSSAT. Additionally, a weather file was created for 30 years (1986–2015) of observed daily minimum and maximum temperature, solar radiation (collected by the nearest synoptic weather station in Natitingou, 63 km from the research site), and rainfall (collected from a nearby rain gauge station in Tanguieta (27 km)). All the data on crop management, growth, and yields collected for the two seasons were used to create the standard DSSAT file formats (*.MZX, *.SGX, *.MZA, *.SGA, *.MZT and *.SGT) for each experiment, needed to run the CERES-Maize and CERES-Sorghum models.

### 2.5. Assessment of models performance

The performance of CERES-Maize and CERES-Sorghum were evaluated graphically by comparing the time series of AGB, soil water and nitrate dynamics, N and P uptake, and final grain and biomass yields from the experiments with predicted values. Statistical assessments to judge the accuracy of model outputs included the root mean square error (RMSE) (Willmott, 1981), normalized-RMSE (nRMSE), and Index of agreements (d) (Yang et al., 2014). These indicators were computed as:

$$\mathrm{RMSE} = \left[\sum_{i=1}^{N} \frac{(Yi - Xi)^2}{N}\right]^{1/2} \quad (1)$$

$$\mathrm{nRMSE} = \frac{\mathrm{RMSE}}{\overline{X}} * 100 \quad (2)$$

$$\mathrm{d} = 1 - \frac{\sum_{i=1}^{N} (Yi - Xi)^2}{\sum_{i=1}^{N} (|(Yi - \overline{X})| + |Xi - \overline{Y}|)^2} \quad (3)$$

where N is number of observations, Yi is the predicted value for the $i^{th}$ measurement, Xi is the observed value for the $i^{th}$ measurement, $\overline{Y}$ is the mean of the predicted values, and $\overline{X}$ is the mean of the observed values. When predicted values exactly fitted the observed values, RMSE and nRMSE are 0 and the corresponding d-value is 1. The criteria of agreement between observed and predicted values were set according to Yang et al. (2014): the predictions of the models were considered accurate when evidenced by the lowest RMSE and nRMSE and with $d \geq 0.75$ for the outputs of the yield components. The minimum criterion $d \geq 0.60$ was set as threshold for the acceptance of the accuracy of predictions in soil-plant N and P and water dynamics.

### 2.6. Simulations of effects of different soil fertility management strategies

The validated CERES-Maize and CERES-Sorghum models were

**Table 4**
Soil hydraulic properties after calibration and used during models simulations in experiment-2.

| Hydraulic properties | Starting points per soil depth | | | Optimized values per soil depth | | |
|---|---|---|---|---|---|---|
| | 20 cm | 40 cm | 60 cm | 20 cm | 40 cm | 60 cm |
| LL ($cm^3\ cm^{-3}$) | 0.046 | 0.055 | 0.084 | 0.050 | 0.085 | 0.090 |
| DUL ($cm^3\ cm^{-3}$) | 0.116 | 0.118 | 0.147 | 0.205 | 0.254 | 0.292 |
| SAT ($cm^3\ cm^{-3}$) | 0.435 | 0.461 | 0.433 | 0.280 | 0.310 | 0.390 |
| SWCN ($cm\ h^{-1}$) | 6.110 | 6.110 | 2.590 | 5.500 | 3.650 | 2.230 |
| WR | 1.000 | 0.549 | 0.368 | 1.000 | 0.749 | 0.468 |
| Other inputs | Default values | Adjusted values | | | | |
| Soil surface albedo (SLAB) | 0.13 | 0.13 | | | | |
| First stage evaporation (U) | 6 | 6 | | | | |
| CN2 | 73 | 70 | | | | |
| SWCON | 0.6 | 0.3 | | | | |

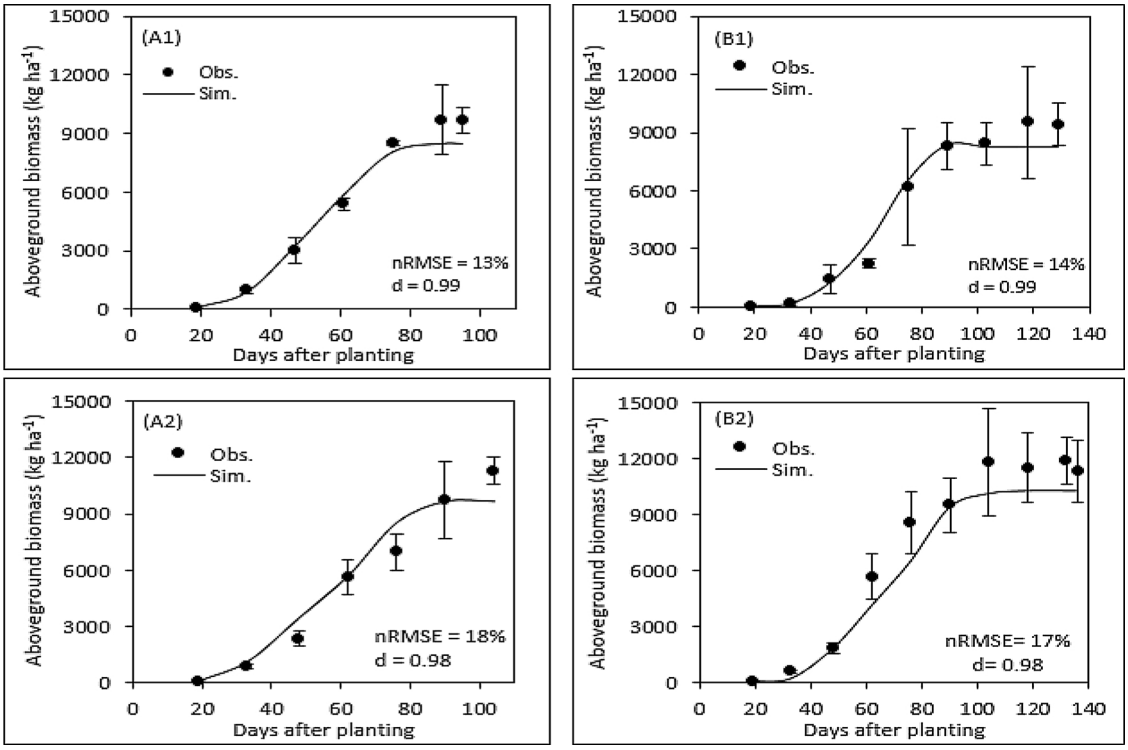


**Fig. 1.** Observed (symbols) and simulated (lines) aboveground biomass changes with time of maize (A1, A2) and sorghum (B1, B2) in experiment-1 during the 2014 (A1, B1) and 2015 (A2, B2) cropping seasons.

finally used to assess the effects of three soil fertility management strategies on soil C and N, water and N use efficiencies, and grain yields of maize and sorghum assuming 30 years of weather variability (1986–2015). The major soil groups on the crests and upper slopes of the inland valleys in the study area are Plinthosols and Luvisols, whilst the major soil type on the lower slopes and extended valley bottom lands in the area is Alisols (Steup, 2016). Hence, the assessment of the effects of soil fertility management strategies were conducted on Alisols since they represent the dominant agriculturally used soil type (IUSS Working and Group, 2014). The three tested options during simulations were (i) the unamended soil as control, (ii) the integrated soil-crop management practice, and (iii) the high use of mineral fertilizer (Section 2.2).

The simulations were conducted using the seasonal analysis option in DSSAT (Hoogenboom et al., 2010) for rainfed maize and sorghum assuming the same initial soil conditions at the beginning of each season. The outputs of the models were evaluated graphically with the cumulative probability function. The outputs for water use efficiency, N-partial productivity, and N-internal utilization efficiency were expressed as grain yield per unit of evapotranspiration [kg grain (mm ET)$^{-1}$], grain yield per N fertilizer applied [kg grain (kg N fertilizer)$^{-1}$], and grain yield per N uptake [kg grain (kg N uptake)$^{-1}$], respectively.

## 3. Results

### 3.1. Weather during the experiments

The total annual rainfall amounted to 937.2 mm in 2014 and 1095.5 mm in 2015. From planting to harvest, rainfall was about 619 mm in 2014 during the growing cycle of maize and sorghum, but in 2015 it amounted to 912 mm for maize and 948 mm for sorghum. The mean annual air temperature was 29.3 °C and 28.9 °C in 2014 and 2015, respectively. The mean annual minimum temperature was 23.4 °C in 2014 and 22.7 °C in 2015. However, the average minimum temperature over the growing cycle of both crops was approximately 24.0 °C in 2014 and 23.0 °C in 2015. The mean annual maximum temperature was 35.1 °C in 2014 and 2015. The average maximum temperature from

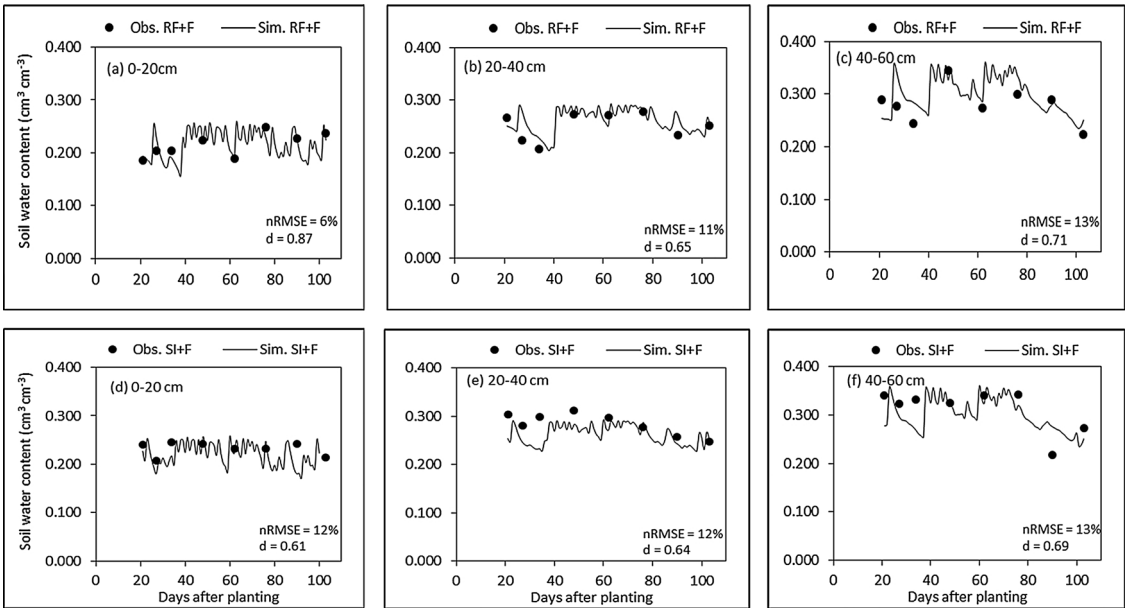


**Fig. 2.** Measured (symbols) and simulated (lines) soil water content under maize rainfed with fertilization (a, b, c) and supplementary irrigation with fertilization (d, e, f) in the 0–20 cm, 20–40 cm, and 40–60 cm soil depths in experiment-2 during the 2015 cropping season.

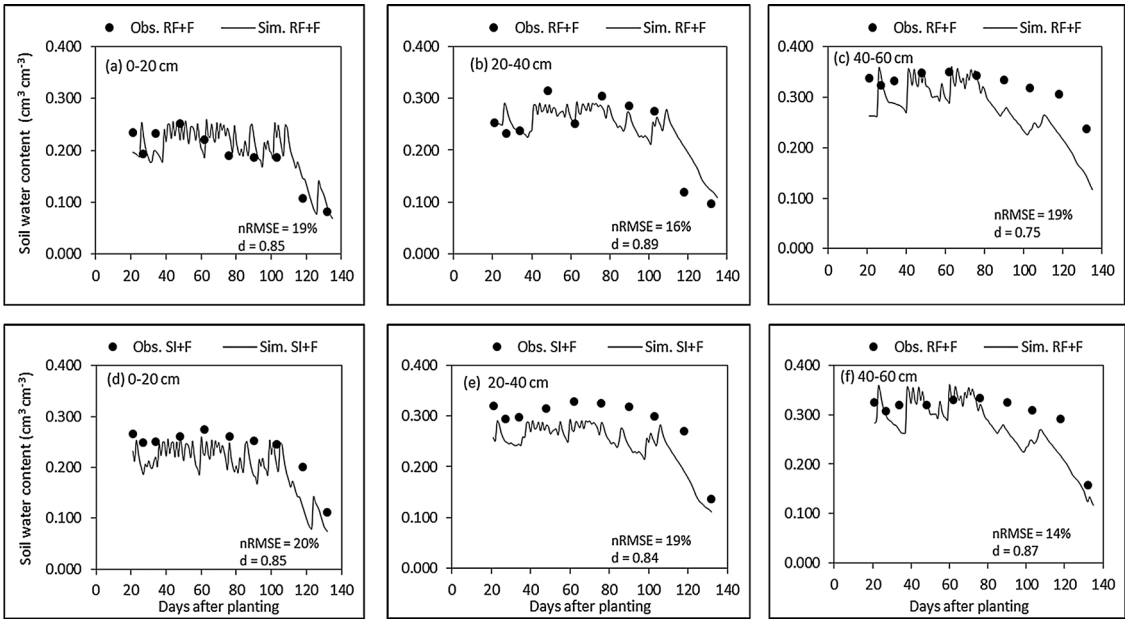


**Fig. 3.** Measured (symbols) and simulated (lines) soil water content under sorghum rainfed with fertilization (a, b, c) and supplementary irrigation with fertilization (d, e, f) in the 0–20 cm, 20–40 cm, and 40–60 cm soil depths in experiment-2 during the 2015 cropping season.

planting to harvest of maize was 32.4 °C while it was 33.0 °C for sorghum in 2014. In 2015, the average maximum temperature was 31.3 °C during the growth cycle of both crops. The average solar radiation was about 18.6 (MJ $m^{-2}$ $d^{-1}$) over the growing cycle of both crops in both growing seasons.

### 3.2. Calibration of models: phenology, biomass, and grain yields

CERES-Maize and CERES-Sorghum predicted accurately phenology of maize and sorghum as monitored in experiment-1 during the 2014 season. CERES-Maize predicted observed anthesis (52 ± 4 DAP) and physiological maturity (80 ± 5 DAP) with RMSE (nRMSE) of 0 day (0%). In 2015, CERES-Maize satisfactorily predicted observed anthesis of maize (53 ± 3 DAP) with RMSE of 1 day and nRMSE of 2%, and physiological maturity (86 ± 4 DAP) with RMSE of 1 day and nRMSE of 1%.

In the 2014 season, CERES-Sorghum simulated the observed anthesis (78 ± 8 DAP) with RMSE (nRMSE) of 2 days (3%), and physiological maturity (103 ± 6 DAP) with RMSE (nRMSE) of 0 day (0%). In 2015, CERES-Sorghum predicted fairly well the observed anthesis of sorghum (92 ± 7 DAP) with RMSE (nRMSE) of 14 days (15%), and physiological maturity (123 ± 5 DAP) with RMSE (nRMSE) of 14 days (11%) also.

In the 2014 season, the models predicted accurately the observed AGB accumulation of both maize and sorghum (Fig. 1A1, B1). CERES-Maize simulated the changes in AGB over time with nRMSE of 13% and d-value of 0.99 (Fig. 1A1). Likewise, CERES-Sorghum showed a satisfactory fit between predicted and observed AGB accumulation, as

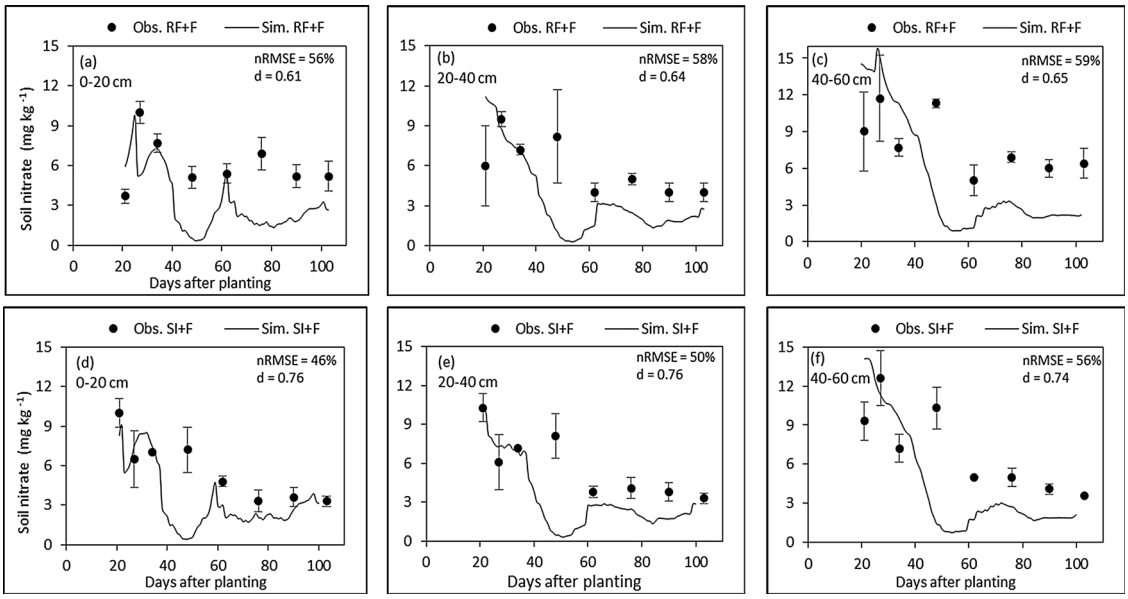


**Fig. 4.** Measured (symbols) and simulated (lines) soil nitrate-nitrogen under maize rainfed with fertilization (a, b, c) and supplementary irrigation with fertilization (d, e, f) in the 0–20 cm, 20–40 cm, and 40–60 cm soil depths in experiment-2 during the 2015 cropping season.

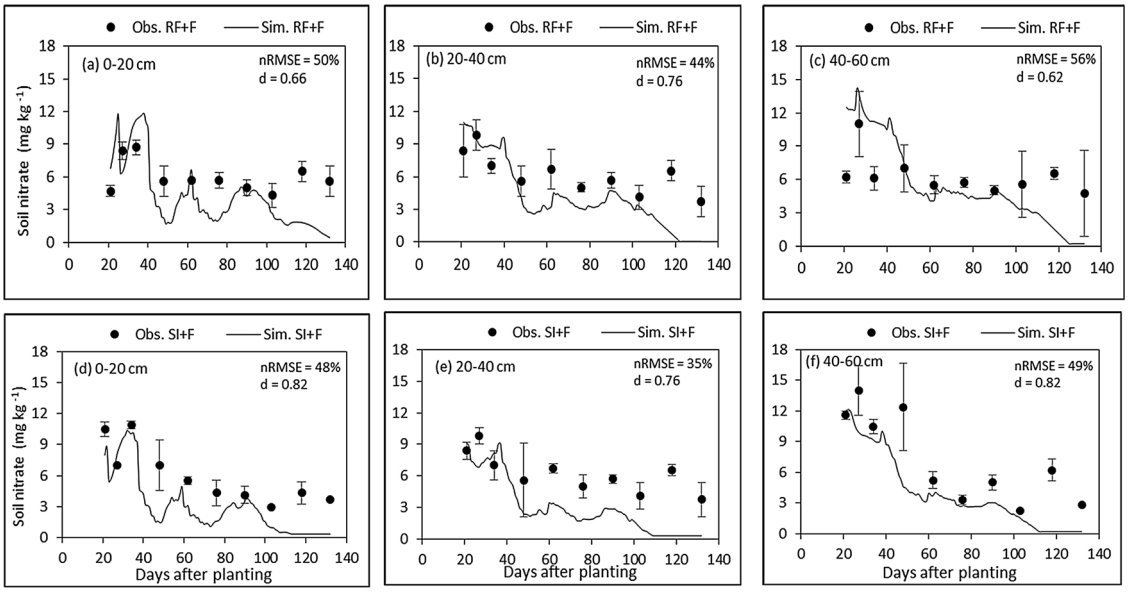


**Fig. 5.** Measured (symbols) and simulated (lines) soil nitrate-nitrogen under sorghum rainfed with fertilization (a, b, c) and supplementary irrigation with fertilization (d, e, f) in the 0–20 cm, 20–40 cm, and 40–60 cm soil depths in experiment-2 during the 2015 cropping season.

evidenced by nRMSE of 14% and d-value of 0.99 (Fig. 1B1). Both parameterized models simulated fairly well the changes in AGB during the 2015 season (Fig. 1A2, B2).

In experiment-1, CERES-Maize predicted the measured biomass (9110 ± 578 kg ha$^{-1}$) and grain yields (2889 ± 159 kg ha$^{-1}$) at harvest in 2014 with RMSE (nRMSE) of 621 kg ha$^{-1}$ (7%) and 47 kg ha$^{-1}$ (2%), respectively. In 2015, CERES-Maize predicted maize biomass yield (9416 ± 567 kg ha$^{-1}$) with RMSE of 253 kg ha$^{-1}$ and nRMSE of 3%, and maize grain yield (3718 ± 363 kg ha$^{-1}$) with RMSE of 252 kg ha$^{-1}$ and nRMSE of 7%.

At final harvest in 2014, sorghum biomass and grain yields were 8265 ± 705 kg ha$^{-1}$ and 1778 ± 157 kg ha$^{-1}$, respectively. The RMSE (nRMSE) between observed and simulated values with CERES-Sorghum was 15 kg ha$^{-1}$ (0.2%) for biomass and 44 kg ha$^{-1}$ (2%) for grain yields. In the 2015 season, CERES-Sorghum simulated observed biomass yield (11623 ± 1780 kg ha$^{-1}$) with RMSE of 1342 kg ha$^{-1}$ and nRMSE of 25%, and grain yield (2456 ± 168 kg ha$^{-1}$) with RMSE of 510 kg ha$^{-1}$ and nRMSE of 21%.

### 3.3. Evaluation of models

#### 3.3.1. In-season soil water dynamics

Measured and simulated soil water contents in various layers of the soil profile are shown for experiment-2 in the 2015 season (Figs. 2 and 3). Under rainfed and supplementary irrigation conditions with fertilizer application, CERES-Maize predicted accurately in-season soil water dynamics in all layers (Fig. 2). CERES-Sorghum predicted reasonably well changes in soil water content in the top 0–20 and 20–40 cm of the soil profile under rain-fed conditions, but tended to under-predict soil water from 70 DAP onwards in the 40–60-cm layer under rainfed conditions and in all layers with supplementary irrigation (Fig. 3).

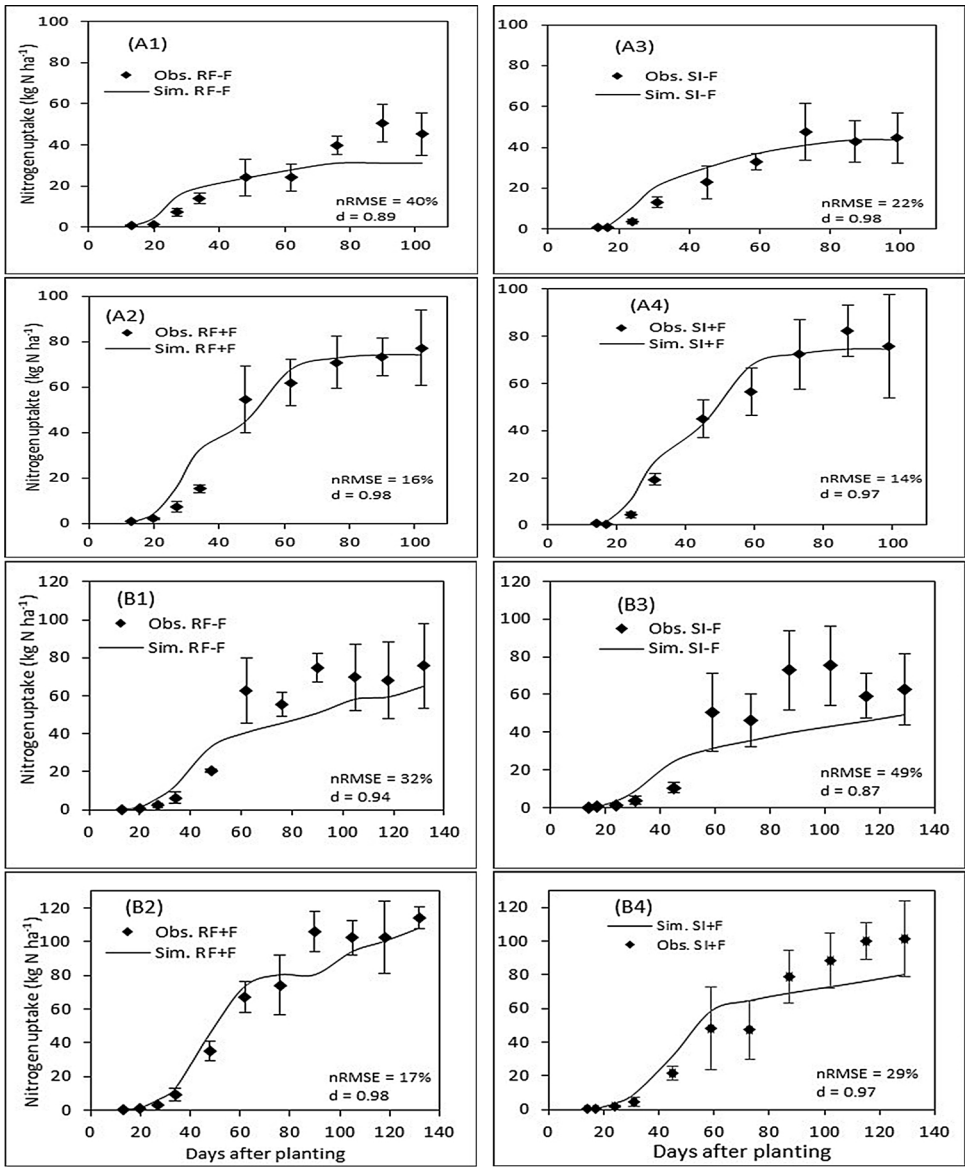


**Fig. 6.** Observed (symbols) and simulated (lines) nitrogen (N) uptake over time by maize (A1, A2, A3, A4) and sorghum (B1, B2, B3, B4) under rainfed without fertilization (RF-F), rainfed with fertilization (RF + F), supplementary irrigation without fertilization (SI-F), and supplementary irrigation with fertilization (SI + F) in experiment-2 during the 2015 cropping season.

### 3.3.2. *In-season soil nitrate-nitrogen dynamics*

Both CERES-Maize and CERES-Sorghum captured fairly well the pattern of soil nitrate-nitrogen dynamics under rainfed and supplementary irrigation conditions with fertilization in experiment-2 (Figs. 4 and 5), but both models differed in accuracy. CERES-Maize predicted early season dynamics (up to 30 DAP) fairly well, but tended to underpredict the dynamics from mid- to the end of the season (Fig. 4). CERES-Maize mimicked in-season nitrate-nitrogen dynamics under rainfed with fertilization conditions with nRMSE of 56–59% and d-values between 0.61 and 0.69 (Fig. 4a, b, c). CERES-Maize predictions were slightly better with supplementary irrigation as shown by lower nRMSE and (d values) ranging from 46 to 56% (0.74–0.76) (Fig. 4d, e, f). Under rainfed conditions, CERES-Sorghum predicted in-season nitrate-nitrogen dynamics with nRMSE of 44–56% and d-values of 0.62–0.76 (Fig. 5a, b, c). Predictions of CERES-Sorghum were relatively better under supplementary irrigation conditions (nRMSE = 35–49%; d = 0.76–0.82) (Fig. 5d, e, f).

### 3.3.3. *Nitrogen and phosphorus uptake*

Under rainfed conditions without fertilization, CERES-Maize overpredicted early-season N uptake, but under-predicted N uptake later in the season (Fig. 6A1). With fertilization, CERES-Maize accurately predicted the end of season N uptake (Fig. 6A2). Under supplementary irrigation, the model simulated the observed N uptake satisfactorily for the treatments both with and without fertilization (Fig. 6A3, A4).

Without fertilization, CERES-Sorghum over-predicted early-season, but under-predicted late-season, N uptake under rain-fed (Fig. 6B1) and supplementary irrigation conditions (Fig. 6B3). With fertilizer application, CERES-Sorghum predicted N uptake over time much more accurately under rainfed (Fig. 6B2) and supplementary irrigation (Fig. 6B4).

Under rainfed conditions without fertilization, CERES-Maize overpredicted P uptake early in the season, and under-predicted P uptake later in the season (Fig. 7A1). With fertilizer application, CERES-Maize predicted P uptake accurately under rainfed conditions (Fig. 7A2). Under supplementary irrigation, with and without fertilization, P uptake was simulated by CERES-Maize satisfactorily (Fig. 7A3, 4). CERES-Sorghum captured P uptake patterns well early in the season, but under-predicted this later in the season under both rain-fed and supplementary irrigated sorghum and with and without fertilization (Fig. 7B1, B2, B3, B4).

### 3.3.4. *Aboveground biomass accumulation*

Under rainfed and supplementary irrigation conditions in

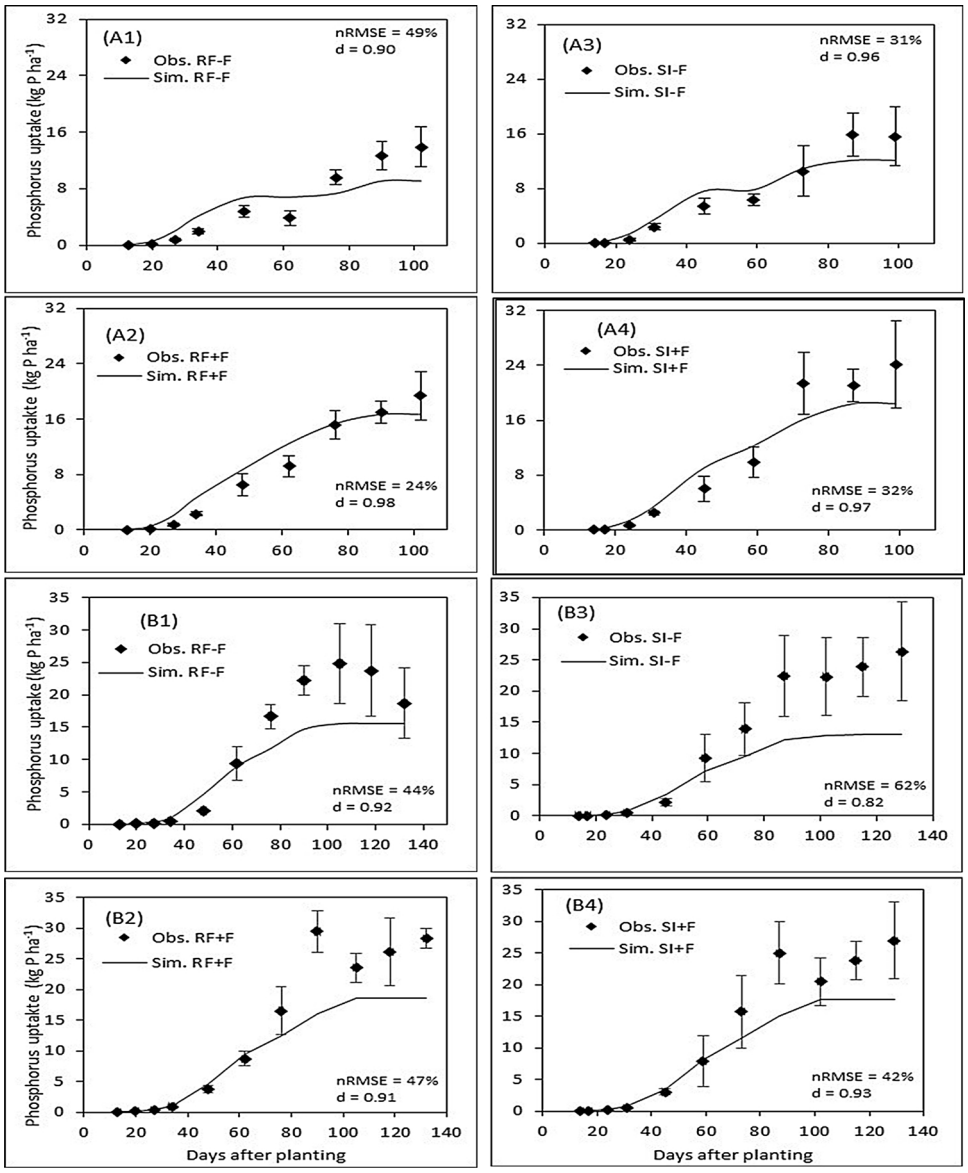


**Fig. 7.** Observed (symbols) and simulated (lines) phosphorus (P) uptake over time by maize (A1, A2, A3, A4) and sorghum (B1, B2, B3, B4) under rainfed without fertilization (RF-F), rainfed with fertilization (RF + F), supplementary irrigation without fertilization (SI-F), and supplementary irrigation with fertilization (SI + F) in experiment-2 during the 2015 cropping season.

experiment-2, with and without fertilization, CERES-Maize predicted AGB with nRMSE of 10–22% and d-values ranging from 0.96 to 0.99 (Fig. 8A1, A2, A3, A4). CERES-Sorghum predicted accurately AGB with nRMSE ranging from 13 to 29% and d-values from 0.97 to 0.99 (Fig. 8B1, B2, B3, B4).

### 3.3.5. Yields at final harvest

In experiment-2, CERES-Maize predicted the final biomass very well given the nRMSE of 16% and d-value of 0.94 (Fig. 9a). CERES-Sorghum simulated the final AGB biomass almost equally well (nRMSE of 14% and d-value of 0.87 (Fig. 9b).

On farmers' fields (experiment-3), CERES-Maize predicted the observed final biomass satisfactorily (Fig. 10a) with nRMSE of 17% and d-value of 0.92. CERES-Sorghum showed only a moderate goodness of fit of AGB yield at final harvest (Fig. 10b) with nRMSE of 45% and d-value of 0.55.

Under the researcher-managed conditions of experiment-2, maize grain yield was predicted with RMSE of 413.6 kg ha$^{-1}$ (nRMSE = 19% and d = 0.93) (Fig. 11a), while sorghum grain yield was predicted with RMSE of 341.2 kg ha$^{-1}$ (nRMSE = 16% and d = 0.91) (Fig. 11b), and hence both predictions were sufficiently accurate.

In the farmer-managed trials (experiment-3), both models predicted grain yield with greater accuracy than AGB (Fig. 12). CERES-Maize predicted maize grain yield more accurately with RMSE of 243 kg ha$^{-1}$, nRMSE of 15%, and d-value of 0.89 (Fig. 12a). Similarly, CERES-Sorghum predicted sorghum grain yield reasonably well with RMSE of 117 kg ha$^{-1}$, nRMSE of 15% and d-value 0.80 (Fig. 12b).

## 3.4. Application of models

### 3.4.1. Effects of soil fertility management on soil carbon and inorganic nitrogen

Fig. 13A1 and B1 show within season differences of soil organic C accumulation, but no long-term trend in soil organic matter. The cumulative probability function (Fig. 13A1) shows the highest soil total organic C with integrated soil-crop management (ISC) and the lowest under un-amended soil (CONT) and high mineral fertilizer use (HMF) in maize production systems. Weather variability hardly altered the total organic C under CONT and HMF, but resulted in noticeable changes with ISC, particularly after 0.90 cumulative probability. In sorghum production systems, the simulated total organic C was different between the three soil fertility management strategies. Total soil organic C

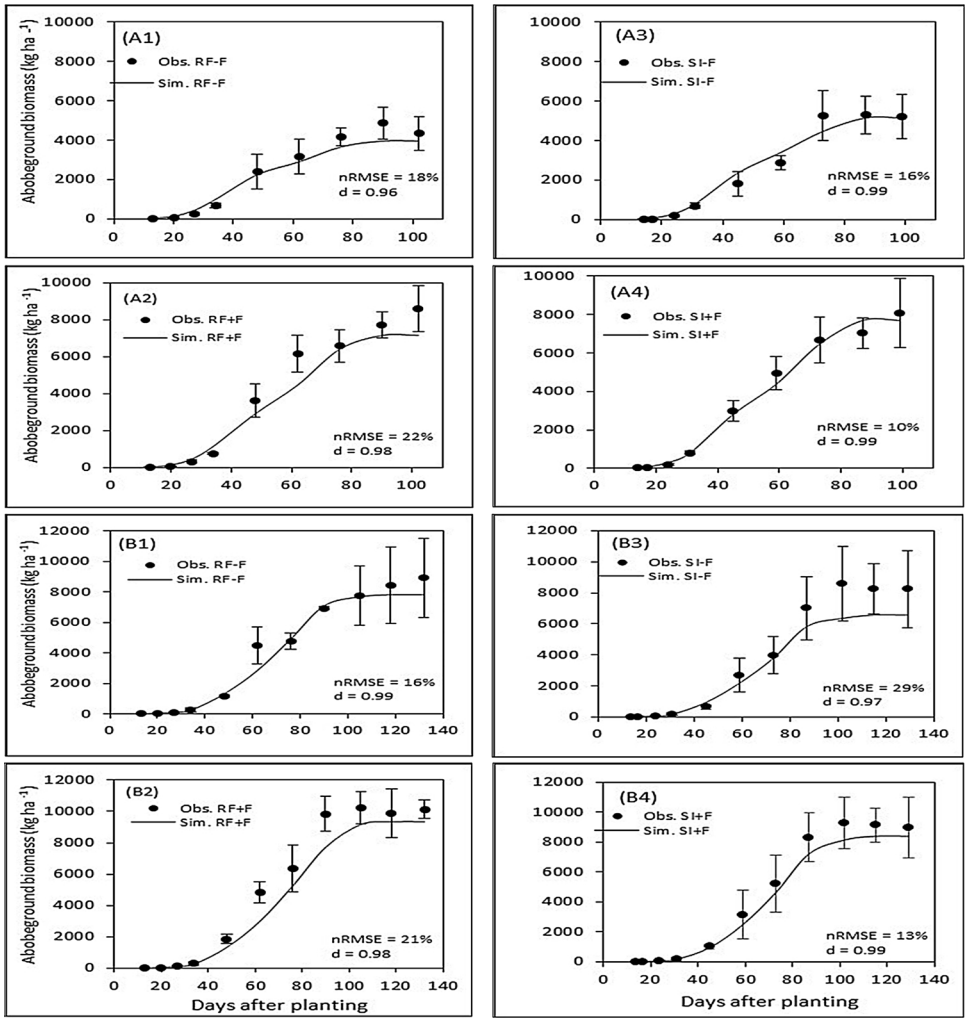


**Fig. 8.** Observed (symbols) and simulated (lines) changes in aboveground biomass of maize (A1, A2, A3, A4) and sorghum (B1, B2, B3, B4) under rainfed without (RF-F) and with fertilization (RF + F), and supplementary irrigation without (SI-F) and with fertilization (SI + F) in experiment- 2 during the 2015 cropping season.

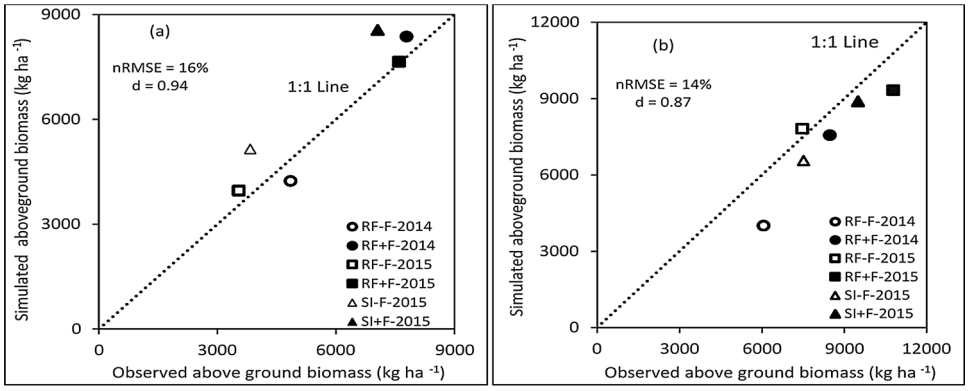


**Fig. 9.** Observed and simulated aboveground biomass at final harvest for maize (a) and sorghum (b) under rainfed and supplementary irrigation without (open symbols) and with fertilization (solid symbols) in experiment-2 for the 2014 and 2015 cropping seasons.

was highest with ISC and lowest with HMF (Fig. 13B1).

Soil inorganic N in maize production systems was affected by soil fertility management strategies and weather variability (Fig. 13A2). Higher soil inorganic N was predicted with ISC compared to the CONT and HMF. The simulated inorganic N showed similar patterns under CONT and HMF up to 0.90 cumulative probability while considerable variability appeared with ISC from approximately 0.50 cumulative probability onwards. The cumulative probability function of the simulated inorganic N under sorghum production systems indicates no substantial difference between the treatments till 0.40 (Fig. 13B2). Thereafter, predicted inorganic N in ISC became higher than with CONT or HMF.

### 3.4.2. Options for improving water use efficiency

The cumulative probability function (Fig. 14A1, B1) demonstrates that simulated water use efficiency of maize (Fig. 14A1) and sorghum (Fig. 14B1) were higher under ISC and HMF, and lower with CONT. The effects of weather variability were substantial within soil fertility management strategies as evidenced by maize water use efficiency fluctuations ranging from 1.8 to -6.3 kg grain (mm ET)$^{-1}$ with CONT, 7.3–11.1 kg grain (mm ET)$^{-1}$ under ISC, and 4.4–11.6 kg grain (mm ET)$^{-1}$ in HMF. For sorghum, the variability in water use efficiency between years was within the range of 1.7–5.0 kg grain (mm ET)$^{-1}$, 5.4–8.7 kg grain (mm ET)$^{-1}$, and 5.0–7.9 kg grain (mm ET)$^{-1}$ under CONT, ISC, and HMF, respectively.

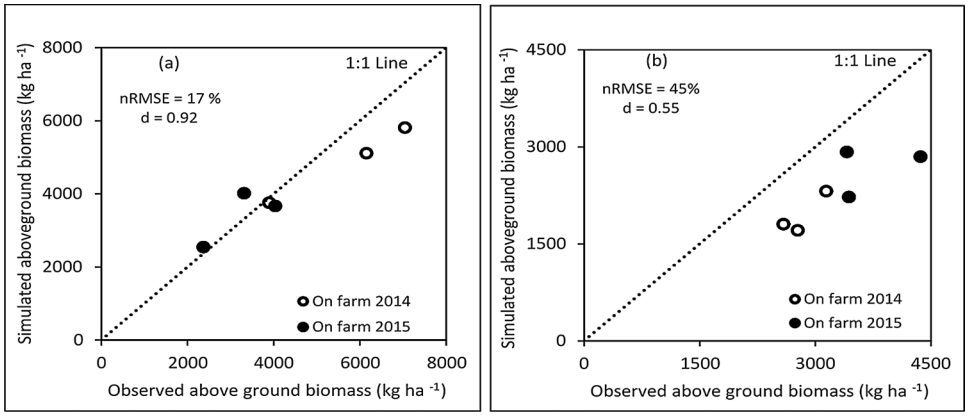


**Fig. 10.** Observed and simulated aboveground biomass at final harvest for maize (a) and sorghum (b) under farmer field conditions (experiment-3) during the 2014 (open symbols) and 2015 (solid symbols) cropping seasons.

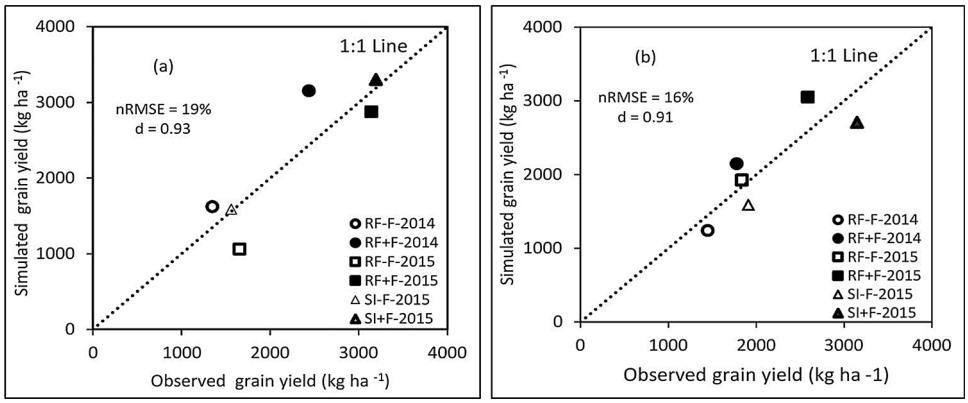


**Fig. 11.** Observed and simulated final grain yields for maize (a) and sorghum (b) under rainfed and supplementary irrigation without (open symbols) and with fertilization (solid symbols) in experiment-2 for the 2014 and 2015 cropping seasons.

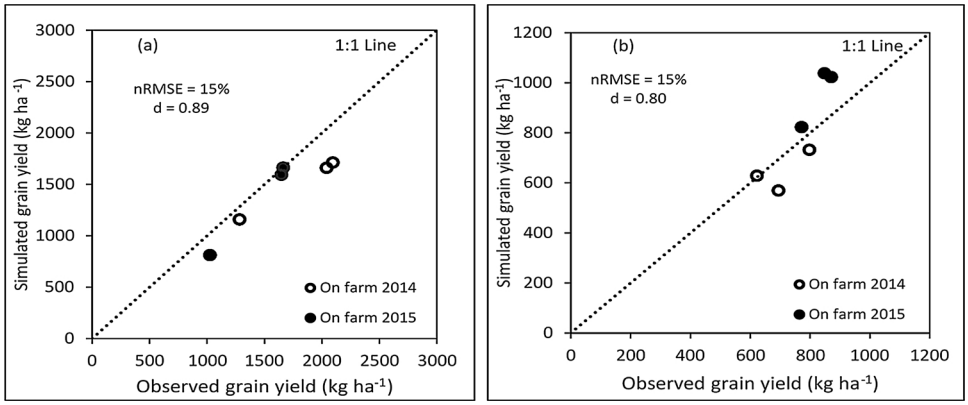


**Fig. 12.** Observed and simulated grain yield at final harvest for maize (a) and sorghum (b) under farmer conditions (experiment-3) during the 2014 (open symbols) and 2015 (solid symbols) cropping seasons.

### *3.4.3. Options for improving N use efficiency*

Simulated grain yield of maize or sorghum gained per unit of N fertilizer applied (N-partial factor productivity, N-PFP) with ISC was significantly higher than that in HMF (Fig. 14A2, B2). Maize grain yield per N uptake (N-internal utilization efficiency, N-IE) was hardly different due to soil management strategies up to approximately 0.50 cumulative probability. Thereafter, predicted N-IE of maize became greater under both CONT and HMF compared to ISC. However, from 0.80 to 1.0 cumulative probability, N-IE of maize under CONT was the highest (Fig. 14A3). Simulated N-IE of sorghum for CONT was as high as with HMF, but greater than that with ISC. Substantial effects of weather variability were simulated by CERES-Maize and CERES-Sorghum on N-PFP and IE between years (Fig. 14A2, A3 and B2, B3).

## 4. Discussion

Crop simulation models are essential tools to support the design of resilient production systems not only under on-going climate variability but also assuming future climate and agricultural land use change. Many features of crop production in the West African dry savanna challenge available crop models including the handling of nutrient deficiencies and biotic stresses. Any confidence in model predictions must be based on their ability to successfully predict performance as monitored in practice especially under the strongly contrasting environmental conditions observed in the tropics in general and in West Africa in particular. This study provides evidence on the capability of CERES-Maize and CERES-Sorghum to simulate growth, yields, dynamics of soil water, as well as N and P uptake in response to seasonal soil moisture availability and soil-crop management systems under the dry savanna agro-ecological conditions. The results confirm earlier findings on the suitability of CERES-Maize and CERES-sorghum to simulate growth, development, and yield of maize (Dzotsi et al., 2003; Igue et al., 2013; Jagtap et al., 1993; McCarthy et al., 2012), and sorghum (McCarthy et al., 2010; Singh et al., 2014) in West Africa. Both

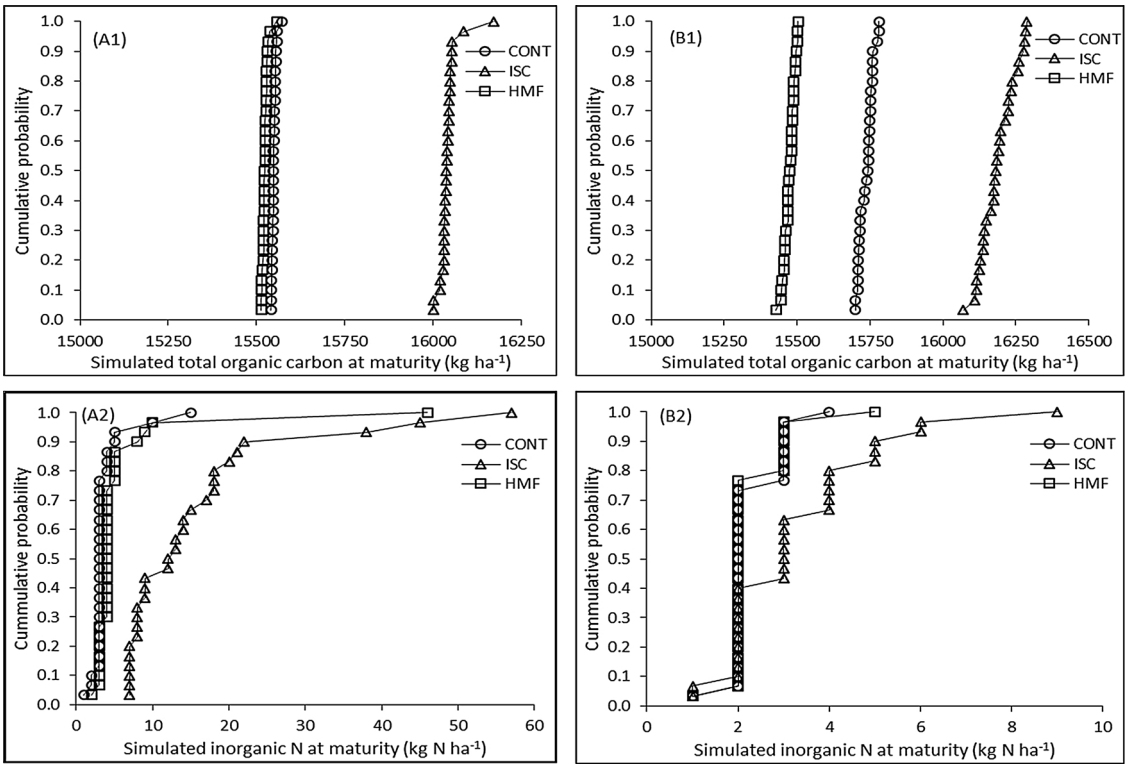


**Fig. 13.** Cumulative probability function of simulated total soil organic carbon (A1, B1) and soil inorganic nitrogen (A2, B2) under maize (A1, A2) and sorghum (B1, B2) production systems, assuming an un-amended soil (CONT), integrated soil-crop management (ISC), and a high mineral fertilizer use (HMF) assuming the historic weather variability (from 1986 to 2015).

CERES models predicted grain yields reasonably well also under farmer management practices common in northern Benin that resemble continuous soil mining production systems. Hence, the findings confirm the capability of both models in DSSAT-CSM v4.6 to predict growth and yield of sorghum and maize crops in N and P-deficient environments compared to previous versions as reported earlier (Dzotsi et al., 2010; Porter et al., 2009).

Both CERES-Maize and CERES-Sorghum models have been extensively tested in West Africa in terms of crop growth and yield under both fertilized and unfertilized conditions (Adnan et al., 2017; Fosu et al., 2012; Soler et al., 2011), but less so in terms of soil water and nutrient dynamics. This study showed that CERES-Maize accurately simulated the changes in soil water in the various layers of the soil profile. Similar good simulations of the soil water balance by CERES-Maize was reported by de Vos and Mallett (1987), Gabrielle et al. (1995), Anothai et al. (2013), and Liu et al. (2013). In contrast, CERES-Sorghum was less accurate for the lower layers due to water extraction presumably by roots at lower soil depth. These results indicate that the calibration of the models for various soil hydraulic parameters resulted in a satisfactory simulation of the soil water balance of CERES-Maize, but the root weighting parameter may not have been appropriate for the CERES-Sorghum model.

Although it has been postulated that early-seasonal soil moisture dynamics in particular trigger N and P supply and their uptake by crops (Bationo et al., 2012; Buerkert and Hiernaux, 1998; Schlecht et al., 2007), few studies if any, have modeled these processes in DSSAT CERES models. Both CERES-Maize and CERES-Sorghum models captured the observed early-season flush of nitrate-nitrogen, but consistently under-predicted soil nitrate-N in all layers as the season progressed. The under-prediction of soil nitrate-nitrogen may have been caused by the influence of soil water availability on mineralization and leaching losses. The nRMSE values ranged from 46 to 59% for CERES-Maize and 35–56% for CERES-Sorghum indicating large uncertainties associated with the simulation of the soil mineral N content, which is not surprising given the complexity of soil N dynamics. Similar uncertainties in simulating soil nitrate-nitrogen were observed by Liu et al. (2011) and Yang et al. (2014). Both CERES-Maize and CERES-Sorghum predicted well the cumulative N and P uptake in the conditions of northern Benin. Differences or similarities in the uptakes patterns under both rainfed and supplementary irrigations conditions could be explained by nutrient concentrations (Figs. 4 and 5), soil water availability (Figs. 2 and 3), and root activity (Godwin and Singh, 1998). Liu et al. (2012) predicted with satisfaction maize growth and its N uptake in northeastern China after optimizing both for the maize cultivar coefficients and N stress coefficients. McCarthy et al. (2010) also reported good performance of CERES-Sorghum for N uptake, but concurrently highlighted the inability of the previous version of CERES-Sorghum to simulate P-dynamics.

The good performance of both models provided a basis for modeling the long-term (30 years of weather variability) impacts of different nutrient management options on soil organic C, inorganic N, water and N use efficiencies in the maize and sorghum-based production systems in the region. According to the simulations of CERES-Maize and CERES-Sorghum, the ISC practice increased soil organic C and inorganic N compared to CONT and HMF as a result from the return of crop residues under ISC contrary to CONT and HMF. Soler et al. (2011) simulated in Burkina Faso a decline in soil organic C under continuous crop rotation (e.g. sorghum) without fertilization and with the removal of aboveground biomass at harvest. The predicted higher soil inorganic N with ISC compared to CONT and HMF, indicated more N release and availability under ISC practices due to mineralization of the incorporated crop residues and soil organic matter (Porter et al., 2009). The models predicted in addition higher year-to-year changes for soil inorganic N compared to organic C changes irrespective of the soil fertility management options tested. This indicates the dominating influence of weather variability, rainfall in particular, and corresponding soil moisture on N release (Unger et al., 2010). The accumulation of soil inorganic N at final harvest under ISC suggests that this integrated

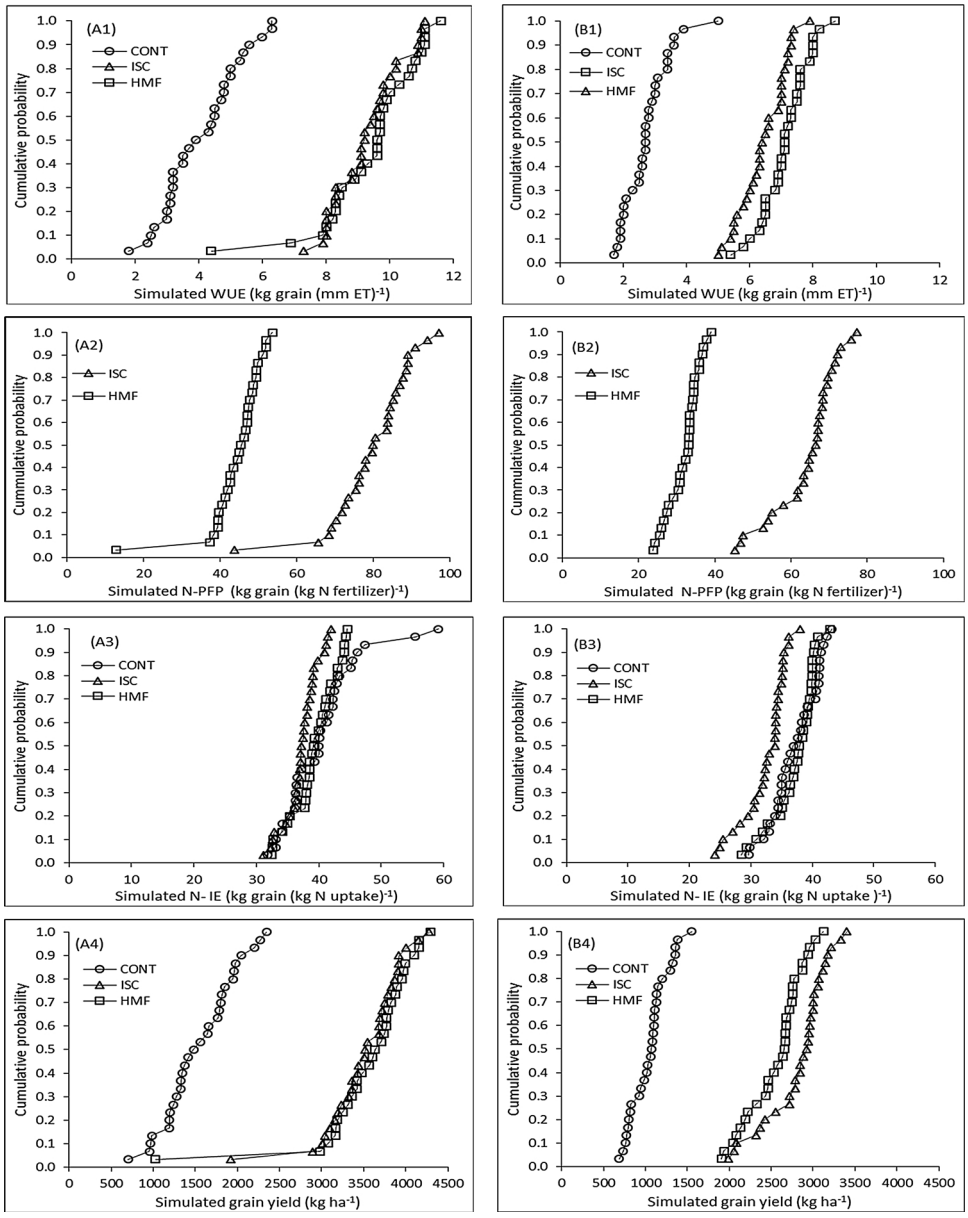


**Fig. 14.** Cumulative probability function of simulated water use efficiency (WUE, A1, B1), N-partial factor productivity (N- PFP, A2, B2), N- internal utilization efficiency (N- IE, A3, B3), and grain yields (A4, B4) of maize (A1, A2, A3, A4) and sorghum (B1, B2, B3, B4) under un-amended soil (CONT), integrated soil-crop management (ISC), and high mineral fertilizer use (HMF) assuming the historic weather variability (from 1986 to 2015).

nutrient management strategy must boost N supply especially at the onset of succeeding season and is thus one option to ease N-stress on crop growth and production.

Soil fertility management options such as ISC and HMF increased in addition water use efficiency (WUE) of both crops. The higher WUE with HMF and ISC compared to the CONT can be explained by the increases in grain yields with HMF and ISC practices with the same amount of water. The present results together with previous findings (McCarthy et al., 2017, 2010; Ritchie and Basso, 2008) confirms that, with a fixed water supply, soil fertility management options that increase yields improve WUE concurrently.

The CERES-Maize and CERES-Sorghum models both simulated greater N-PFP for ISC than HMF. The more efficient N use with ISC is due to the combination of similar grain yields under ISC and HMF and lower amounts of N fertilizer applied under ISC (almost 50% less of N applied compared to HMF). This is in much agreement with earlier findings by McCarthy et al. (2017) who reported higher N-PFP for maize with a combination of inorganic N fertilizer and manure. The predicted N-IE by both models fell on the one hand within the ranges recognized for cereals (Dobermann, 2007). On the other hand, the higher N-EI predicted when assuming CONT points at the increased capability of crops to transform the N previously taken up into grain yield in case of low-N environments (Dobermann, 2007; Wang et al., 2014).

The CERES-Maize predicted no difference in grain yield patterns between ISC and HMF, while CERES-Sorghum simulated the highest sorghum grain yields with ISC. The trends of grain yields obviously are driven by the increased WUE and N-PFP of both crops with favorable soil fertility management strategies such as ISC and HMF. Furthermore, the similar, or even greater grain yields simulated under ISC compared to HMF, highlights once more the importance of crop residue retention in the semi-arid and arid regions of West Africa for a balanced and improved soil fertility and plant nutrition (Buerkert et al., 1996; Lal, 2006). Together with previous findings (e.g. McCarthy et al., 2017, 2010), the current results thus underline that an integration of nutrient applications stemming from various sources (e.g. soil, fertilizers, crops residues, manures, etc.) has the highest potential to result in significant increases in crop yields compared to the use of one practice alone. In addition, an improved nutrient use efficiency results in reduced environmental risks. Such soil fertility management options, recurrently

referred to as “Integrated Soil Fertility Management Strategies”, aimed at enhancing thus both productivity and resource use efficiency, are acknowledged sustainable agriculture practices in the region (Carsky et al., 1999; Sanginga and Woomer 2009; Vanlauwe et al., 2014). These options are thus highly needed for the dry savanna agro-ecological zone of Benin to ensure sustainable resource use and crop productivity. The year-to-year variability in grain yields under the same soil fertility management strategy was caused mainly by changes in key weather parameters such as intra-annual rainfall. This became crucial because the maximum temperatures during the growing cycle remained below the optimum temperature (34 °C) of both crops (Kumudini et al., 2014; White et al., 2015) thus excluding heat-stress effects. The model findings reinforce thus the potential of increasing food security in West Africa by sustainable agriculture management. These findings should support decision making for defining future nutrient markets in West Africa and provide research-based evidence on the level of resilience and sustainability of production systems, which may be of interest to decision makers and farmers alike.

## 5. Conclusions

The CERES-Maize and CERES-Sorghum models predicted with satisfaction yield components and the underlying soil water and plant N and P demands under current weather conditions. While assuming the long-term weather scenario, both models predicted increased soil C and N, water- and N- use efficiencies, and grain yields under the integrated soil-crop management practice compared to un-amended soil and high rates of mineral fertilizer use. Since the models realistically predicted seasonal soil water and nitrate-nitrogen dynamics in both maize- and sorghum-based productions systems in northern Benin, it can be concluded that both models perform well in water- and nutrient-stress-free as well as nutrient-deficient crop production environments. This evidences the robustness of the CERES-Cropping System models to perform under dry savanna agro-ecological conditions as prevail in various parts of West Africa. Consequently, both models are appropriate tools for exploring potential impacts of predicted climate change on soil water and nutrient use efficiencies. Such findings should support the identification of sustainable production and intensification options for the maize- and sorghum-based production systems of West Africa that would be more resilient under future climate variability and thus support better-informed decision-making.

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